Gamma-Ray Burst Light Curve Reconstruction: A Comparative Machine and Deep Learning Analysis

Gamma-Ray Bursts (GRBs) are the most powerful explosions in the universe, detectable from billions of light-years away. This unique property makes them exceptional **cosmological tools**—potential "standard candles" that can be used to measure cosmic expansion and probe the early universe, even beyond the range of Type Ia supernovae.

The Challenge: Gaps in the Data

To use GRBs for cosmology, scientists rely on precise correlations, such as the **Dainotti relation**, which links the luminosity of a GRB's afterglow plateau to its duration. However, the data we collect from space-based observatories like the *Neil Gehrels Swift Observatory* is often incomplete. Satellites in low-Earth orbit cannot stare at a single point indefinitely. Orbital mechanics, Earth blocking the view, and instrumental downtime create **temporal gaps** in the data, or "light curves" (LCs), that track the GRB's brightness over time.

These gaps are a major problem. They introduce significant errors and uncertainties when measuring the key parameters of the GRB plateau, thereby weakening the power of correlations such as the Dainotti relation and closure relations, hindering our ability to test theoretical models.

The Solution: AI-Powered Reconstruction

This research provides a powerful new solution by leveraging **machine learning (ML) and deep learning (DL)** to perform Light Curve Reconstruction (LCR). The goal is to intelligently "fill in" the missing data gaps, creating a more complete and continuous light curve. This, in turn, allows for a much more precise measurement of the key physical parameters:

- **log Ta**: The end time of the plateau emission.
- **log Fa**: The flux (related to luminosity) at the end of the plateau.
- **α**: The decay slope of the light curve after the plateau ends.

A Comparative Analysis

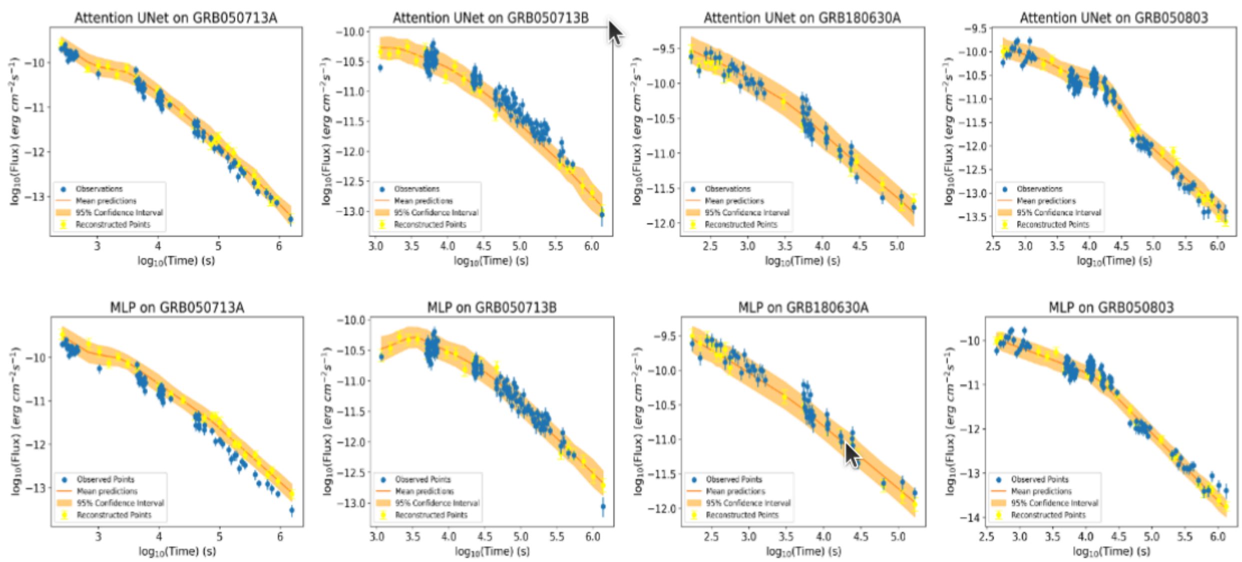
The research team conducted a comprehensive analysis on a large dataset of **521 GRBs**. They trained and tested **nine different ML and DL models**, comparing their performance against each other and the standard Willingale (W07) model. The nine models included: Multi-Layer Perceptron (MLP), Attention U-Net, Bi-Mamba, Bidirectional Long Short-Term Memory (Bi-LSTM), Kolmogorov-Arnold Networks (KANs), Conditional GAN (CGAN), Gaussian Process-Random Forest Hybrid (GP-RF), SARIMAX-based Kalman filter and Fourier Transform.

Key Results: MLP and Attention U-Net

The study evaluated the models on two primary criteria: **accuracy** (lowest 5-fold cross-validation Mean Squared Error, or MSE) and **precision** (the greatest percentage reduction in the uncertainty of the physical parameters log Ta, log Fa, and α). Two models emerged as clear front-runners: **MLP** and the **Attention U-Net**.

Model	Key Strength	Test MSE	% Uncertainty Reduction (log Ta)	% Uncertainty Reduction (log Fa)	% Uncertainty Reduction (α)
MLP	**Most Reliable (Best Accuracy)**	**0.0275**	37.2%	38.0%	41.2%
Attention U-Net	**Most Precise (Best Precision)**	0.134	**37.9%**	**38.5%**	**41.4%**
GP (W07)	Baseline	3.63	24.3%	18.6%	16.9%

Here we show the reconstruction with the MLP and the Attention U-Net model:



Significance & Impact: Why This Matters

This research provides a new, validated toolkit for the entire astrophysics community, with profound implications.

- **For Cosmology:** By reducing the uncertainty in log Ta and log Fa by over 38%, these models make the **Dainotti relation** a much stronger and more reliable cosmological tool. This is a critical step toward using GRBs as precision **standard candles** to measure the expansion of the universe.
- **For Astrophysics:** The post-plateau slope, αa, is essential for testing theoretical models of GRB physics, such as the **standard fireball model**. By reducing the uncertainty of this parameter by over 41%, these new LCR models allow for much stricter and more meaningful tests of these fundamental theories.
- **For Future Missions:** The framework developed in this study can be extended to analyze data from upcoming missions like SVOM, Einstein Probe, and THESEUS, as well as data from other wavelengths, such as optical LCs.